

KNN Variants for Text Summarization using Feature Similarity

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Abstract—In this research, we propose the KNN variants which consider the feature similarities and apply them to the text summarization. The initial KNN version was previously modified into one which considered the feature similarities and applied to the task by mapping it into a binary classification. In this research, we mention the three KNN variants, in the case of the numerical vector-based versions: one where the selected nearest neighbors are discriminated by their similarities, one where the attributes are discriminated by their correlations with the categories, and where the training examples are discriminated by their credits. In this research, the three KNN variants are modified so as well as the initial KNN version. This research is aimed to improve the text summarization performance by modifying them so.

I. INTRODUCTION

The text summarization is defined as the extraction of sentences or paragraphs which reflect important contents from a text. A single text is given as the input, and some paragraphs or some sentences are generated as its summary. The text summarization is interpreted into the binary classification of each paragraph into summary or non-summary, and a machine learning algorithm is applied to the binary classification. The process of text summarization is to partition a text into paragraphs, and classify each paragraph so, and extract paragraphs which are classified into summary. The summary which consists of some paragraphs may be used for reinforcing the performance of the text categorization.

This research is motivated by the successful results from using the KNN algorithm which considers the feature similarities for the text summarization. The poor discrimination among sparse numerical vectors which represent texts is solved by using the semantic dependencies among features for defining the similarity metric between two numerical vectors. The KNN algorithm was modified as the approach to the text summarization, using the similarity metric between two numerical vectors. The modified version of KNN algorithm was empirically validated as its better approach to the text summarization, than the traditional version. The differences of this research from the previous work are the modification of the KNN variants into the versions which consider the feature similarities and the application of them to the text summarization.

The idea of this research is to modify the KNN variants into their feature similarity-based versions and apply them

to the text summarization. The similarity metric between numerical vectors which was used for modifying the KNN algorithm is adopted for modifying the KNN variants. The three KNN variants which are proposed in this research are one where the nearest neighbors are discriminated by their distances, one where the attributes are discriminated in computing a similarity between two numerical vectors by their correlations with the target output values, and one where the training examples are discriminated by their quality. The text summarization is mapped into a binary classification of paragraphs, the KNN variants are modified into the versions which consider the feature similarities, and they are applied to the binary classification. Their better performance is expected in the text summarization than the traditional KNN variants and the feature similarity based KNN algorithm.

Let us mention some benefits from this research. The poor discrimination among numerical vectors from their sparseness is solved by proposing the similarity metric between numerical vectors which considers the feature similarities. The classification performance is improved by replacing the KNN algorithm by the KNN variants where the nearest neighbors, the training examples, or the attributes are discriminated. Additionally, it is improved by modifying the KNN variants into the feature similarity-based versions. We provide the more recommendable approaches for implementing the text summarization system by improving the classification performance with the dual steps.

Let us mention the organization of this paper. In Section II, we explore the previous works which are relevant to this study. In Section III, we describe in detail what is proposed in this research. In Section IV, we mention the significances of this research and the remaining tasks. This paper is composed of the four sections.

II. PREVIOUS WORKS

This section is concerned with the previous works which are relevant to this research. It is intended to expand the style of modifying the KNN algorithm to its three variants and apply them to the text summarization. The directions of exploring previous works are derivation of KNN variants, modification and application of the standard KNN algorithm to the text summarization, and the cases of using the feature

similarities for improving machine learning algorithms. The distinguishable points of this research are derivation of three KNN variants from the standard version, modification of them with the feature similarities, and application of them to the text summarization. This section is intended to explore previous works for providing the background for this research.

Let us explore the previous works on KNN variants. In 2001, the KNN variant where nearest neighbors are discriminated by their distances from or similarities as a novice item was applied to the text classification by Han et al. [1]. In 2008, MKNN (Modified K Nearest Neighbor) the KNN variants where training examples are discriminated by their validness, was proposed by Parvin et al. [3]. In 2018, the KNN variant where the attributes are discriminated by their correlations were proposed by Nababan and Sitompul [7]. However, this research uses different specific metrics for discriminating attributes, nearest neighbors, and training examples.

Let us explore the previous works on applying the modified version of KNN algorithm to the text summarization. In 2017, it was initially proposed that the modified version of KNN algorithm should be applied to the text summarization by Jo [4]. In 2019, the modified KNN algorithm was validated in the task by Jo [9]. In 2023, a journal article which describes in detail the modified KNN algorithm and its application to the text segmentation as well as text summarization is prepared for its publication by Jo [10]. This research is based on the three previous works.

Let us mention the previous works on the cases of using the feature similarities as the basis for modifying the KNN variants in this research. In 2002, feature similarities were used for selecting some features for using unsupervised learning algorithms by Mitra et al. [2]. In 2018, feature similarities were used for modifying the AHC algorithm as an approach to text clustering by Jo [5]. In 2018, the KNN algorithm which was modified based on the feature similarities was used for classifying texts [6]. Feature similarities are used for solving the sparseness in numerical vectors.

Let us mention the differences of this research from the previous works which are explored above. The KNN variants which are mentioned in the previous works do not consider the feature similarities, and in this research, we modify them into their versions which consider the feature similarities. As the expansion of [9], we modify and adopt the KNN variants for implementing the text summarization system. The feature similarities are used for modifying the KNN variants as well as the KNN algorithm and the AHC algorithm as the approach to the task. The modified KNN variants will be described in detail in Section III.

III. PROPOSED WORKS

This section is concerned with what is proposed in this research. In Section III-A, we describe the process of encoding

a text into a numerical vector and the proposed similarity metric. In Section III-B, we describe the standard version of KNN algorithm where the proposed similarity metric is adopted. In Section III-C, we derive the three variants from the standard version. In Section III-D, we present the system architecture of the text summarization system.

A. Encoding Process

This section is concerned with the process of encoding a text into a numerical vector. Words are used as features for encoding a text so, and some are selected from words in a corpus. The similarity between words is computed based on texts with their collocations and is used as the similarity between features. The similarities among features are considered for computing the semantic similarity between texts. In this section, we describe the process of encoding a text into a numerical vector and the process of computing the similarity between texts.

The process of encoding texts into numerical vectors is illustrated in Figure 1. The entire text collection is indexed into a list of words which are feature candidates. Some words are selected as the features by criteria among the feature candidates in the second step. The weights of the selected features in the text are computed as their relationships with the text, as elements of the numerical vector. Refer to [8] for studying the process and the selection criteria in detail.

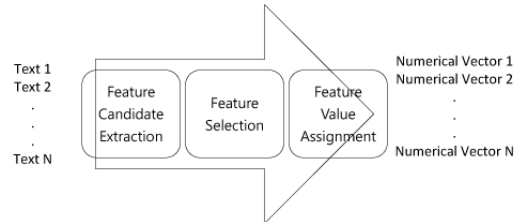


Figure 1. Process of Encoding Words into Numerical Vectors

The frame of computing the similarity between two numerical vectors is illustrated in Figure 2. The two d dimensional vectors and the d features are respectively notated respectively by $\mathbf{x} = [x_1 \ x_2 \ \dots \ x_d]$, $\mathbf{y} = [y_1 \ y_2 \ \dots \ y_d]$, and $f_1, f_2, \dots, f_d$. The feature similarity refers to the similarity between two features, which is notated by $\text{sim}(f_i, f_j)$. The feature value similarity is the similarity between two vectors, $\mathbf{x}$ and $\mathbf{y}$, such as cosine similarity. The similarity between words is computed by considering the two kinds of similarities.

Let us mention the process of computing the similarity between numerical vectors as the similarity between texts. The similarity between the features, f_i and f_j , is notated by $\text{sim}(f_i, f_j) = s_{ij}$. The similarity between the features is computed by equation (1),

$$s_{ij} = \text{sim}(t_i, t_j) = \frac{2 \times \#(t_i \wedge t_j)}{\#(t_i) + \#(t_j)}, \quad (1)$$

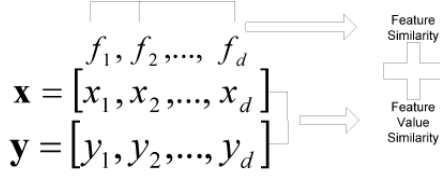


Figure 2. Frame of Computing Similarity between Numerical Vectors

where $\#(t_i \wedge t_j)$, is the number of texts which include both words, t_i and t_j , $\#(t_i)$ is the number of texts which include the word, t_i , and $\#(t_j)$ is the number of texts which include the word, t_j , and the similarity matrix to the d features is constructed as a $d \times d$ square matrix as follows:

$$S = \begin{pmatrix} s_{11} & s_{12} & \dots & s_{1d} \\ s_{21} & s_{22} & \dots & s_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ s_{d1} & s_{d2} & \dots & s_{dd} \end{pmatrix}.$$

The similarity between the two numerical vectors, $\mathbf{x}$ and $\mathbf{y}$, is computed by equation (2),

$$\text{sim}(\mathbf{x}, \mathbf{y}) = \frac{\sum_{i=1}^d \sum_{j=1}^d s_{ij} x_i y_j}{d \|\mathbf{x}\| \|\mathbf{y}\|} \quad (2)$$

Equation (2) is used for computing the similarity between a novice text and a sample text in the KNN algorithm.

Let us make some remarks on the encoding process and the computation of the similarity between two texts. A text is encoded into a numerical vector by the feature candidate extraction, the feature extraction, and the feature value assignment. The similarity between features which are given as words is computed by equation (1). The similarity between numerical vectors which represent texts is computed by equation (2). In future, we consider computing the similarities among some features rather than all features for improving the computation speed.

B. Feature Similarity based KNN Algorithm

This section is concerned with the initial version of KNN algorithm which considers the feature similarities. The version was initially proposed as the approach to the text summarization by Jo in 2019 [9]. The similarity metric between numerical vectors which was described in the previous section is used for computing the similarity between a novice vector and a training example. The labels of its nearest neighbors are voted with their identical weights for decoding the label of a novice vector. This section is intended to describe the initial version of the KNN algorithm from which its variants are derived.

The process of computing the similarity between a novice item and a training example is illustrated in Figure 3. The labeled words which are gathered as samples are encoded

into numerical vectors, and they are notated by a set $Tr = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$. A novice word is encoded into a numerical vector notated by $\mathbf{x}$. Its similarities with the numerical vectors which represent the sample words are computed by equation (2), as $\text{sim}(\mathbf{x}, \mathbf{x}_1), \text{sim}(\mathbf{x}, \mathbf{x}_2), \dots, \text{sim}(\mathbf{x}, \mathbf{x}_N)$. Some training examples which are most similar as the novice input are selected as its nearest neighbors.

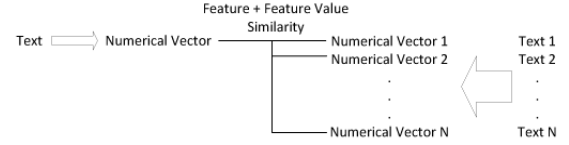


Figure 3. Similarities of Novice Input with Training Examples

In Figure 4, the process of selecting nearest neighbors by the ranking selection is illustrated. The training examples are sorted by the descending order of their similarities, after computing their similarities with a novice example. The training examples with their higher similarities with a novice example are selected as its nearest neighbors, as expressed in equation (3),

$$Nr = \text{Select}_k(Tr, \mathbf{x}), Nr \subseteq Tr \quad (3)$$

The set of nearest neighbors, Nr , is composed with elements as expressed in equation (4),

$$Nr = \{\mathbf{x}_1^{\text{near}}, \mathbf{x}_2^{\text{near}}, \dots, \mathbf{x}_k^{\text{near}}\} \quad (4)$$

The elements in the set, Nr , are used for voting their labels in the next step.

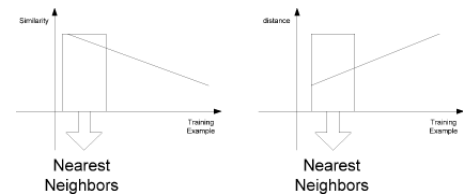


Figure 4. Selection of Most Similar or Least Distant Training Examples as Nearest Neighbors

The process of voting the labels of nearest neighbors for decoding the label of a novice word is illustrated in Figure 5. The predefined categories are notated by $c_1, c_2, \dots, c_m$, and the label of a nearest neighbor is notated by $c_j = \text{label}(\mathbf{x}_i^{\text{near}})$. The number of nearest neighbors which belong to the category, c_j , is notated by $\text{Count}(Nr, c_j)$. The label of the novice item, $\mathbf{x}$, is decided by equation (5),

$$\text{label}(\mathbf{x}) = \underset{j=1}{\text{argmax}}^m \text{Count}(Nr, c_j) \quad (5)$$

The process of deciding the label of a novice item by equation (5), is called voting.

Let us make some remarks on the initial version of KNN algorithm from which we derive some variants. It computes

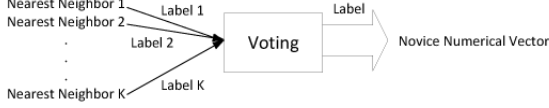


Figure 5. Voting of Labels of Nearest Neighbors for Deciding Label of Novice Input

the similarities of a novice item with the training examples. The training examples with their highest similarities with the novice item are selected as its nearest neighbors. The label of the novice item is decided by voting the labels of its nearest neighbors. The ranking selection is adopted for selecting the nearest neighbors from training examples, in this version.

C. KNN Variants

This section is concerned with the variants which are derived from the KNN algorithm which was covered in Section III-B. The difference from the traditional version is to adopt similarity metric which is expressed in equation (2) for computing the similarity between a novice item and a training example. In this section, we derive the three variants by discriminating nearest neighbors, attributes, or training examples. The three variants of KNN algorithm are adopted for implementing the text summarization system. This section is intended to describe the three variants.

Let us mention the KNN variant which is derived by discriminating the nearest neighbors. A set of nearest neighbors is notated by $Nr = \{\mathbf{x}_1^{near}, \mathbf{x}_2^{near}, \dots, \mathbf{x}_k^{near}\}$, and its elements are assumed as $sim(\mathbf{x}, \mathbf{x}_1^{near}) \geq sim(\mathbf{x}, \mathbf{x}_2^{near}) \geq \dots \geq sim(\mathbf{x}, \mathbf{x}_k^{near})$. The weights, $w_1, w_2, \dots, w_k$, are assigned to the nearest neighbors, $\mathbf{x}_1^{near}, \mathbf{x}_2^{near}, \dots, \mathbf{x}_k^{near}$, following, $w_1 \geq w_2 \geq \dots \geq w_k$, and the total weights are computed for the category, c_j by equation (6),

$$CS(Nr, c_j) = \sum_{\mathbf{x}_i \in Nr} w_i \quad (6)$$

The label of the novice item, $\mathbf{x}$, is decided by equation (7),

$$label(\mathbf{x}) = \arg\max_{j=1}^m CS(Nr, c_j) \quad (7)$$

There are two ways of assigning weights to the nearest neighbors: exponentially decreasing way and arithmetic decreasing way as shown in Figure 6.

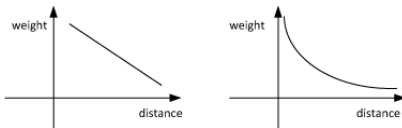


Figure 6. Discrimination over Nearest Neighbors

Let us mention the second KNN variant where the attributes are discriminated for computing the similarity

between a novice item and a training example as shown in Figure 7. If the number of training examples is N , and the dimension of numerical vector representing a training example is d , the attributes are notated as a set, $A = \{A_1, A_2, \dots, A_d\}$, and each attribute is viewed as a set of values, $A_i = \{x_{1i}, x_{2i}, \dots, x_{Ni}\}$. Each class is codified into its own integer, the correlation coefficient between an attribute A_i , and the classes is computed by equation (8),

$$r_i = \frac{\sum_{j=1}^N (x_{ji} - \bar{x}_j)(c_j - \bar{c})}{\sqrt{\sum_{j=1}^N (x_{ji} - \bar{x}_j)^2} \sqrt{\sum_{j=1}^N (c_j - \bar{c})^2}} \quad (8)$$

and the weight, which is assigned to the attribute, A_i , is set by the absolute value of the correlation coefficient, as expressed in equation (9),

$$w_i = |r_i| \quad (9)$$

The similarity between the novice input vector, $\mathbf{x}$ and $\mathbf{x}_i$, is computed by equation (10),

$$sim(\mathbf{x}, \mathbf{x}_i) = \frac{\sum_{j=1}^d \sum_{k=1}^d s_{jk} x_j w_k x_{ik}}{d \cdot \|\mathbf{x}\| \cdot \|\mathbf{x}_i\|}. \quad (10)$$

In this variant, equation (2) is replaced by equation (10) for computing the similarity.

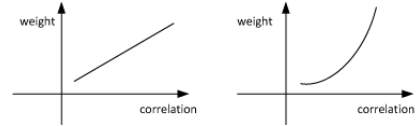


Figure 7. Discrimination over Attributes

Let us mention the third KNN variant where the training examples are discriminated for computing the similarity between a novice item and a training example and/or voting the nearest neighbors for deciding the label as shown in Figure 8. The hypersphere radius is used as the parameter, and for each training example, other training examples are taken within the radius from it as its nearest neighbors. The number of nearest neighbors and the number of training examples which are labeled identically to the training example, $\mathbf{x}_i$, are notated respectively by r_i and r_i^- , and the weight is computed by equation (11),

$$w_i = \frac{r_i^-}{r_i} \quad (11)$$

The similarity between the novice item, $\mathbf{x}$, and the training example, $\mathbf{x}_i$, is computed by equation (12),

$$sim(\mathbf{x}, \mathbf{x}_i) = \frac{w_i \sum_{j=1}^d \sum_{k=1}^d s_{jk} x_j x_{ik}}{d \cdot \|\mathbf{x}\| \cdot \|\mathbf{x}_i\|}. \quad (12)$$

and the total weight is computed for the category, c_j , by equation (13), in voting,

$$CS(Nr, c_j) = \sum_{\mathbf{x}_i \in Nr} w_i \quad (13)$$

Equation (12) and (13) are used respectively for computing the similarity between a novice item and a training example and voting the nearest neighbors for each category.

Figure 8. Discrimination over Training Examples

D. System Architecture

The process of sampling paragraphs domain by domain is illustrated in Figure 9. Even if it is possible map the text summarization into an instance of text classification, a paragraph may be classified differently depending on the domain. Sample paragraphs which are labeled with summary or non-summary are gathered domain by domain. The text which is given as the input is tagged with a domain, and the classifier which corresponds to the domain is appointed. The sample paragraphs are encoded into numerical vectors in each domain.

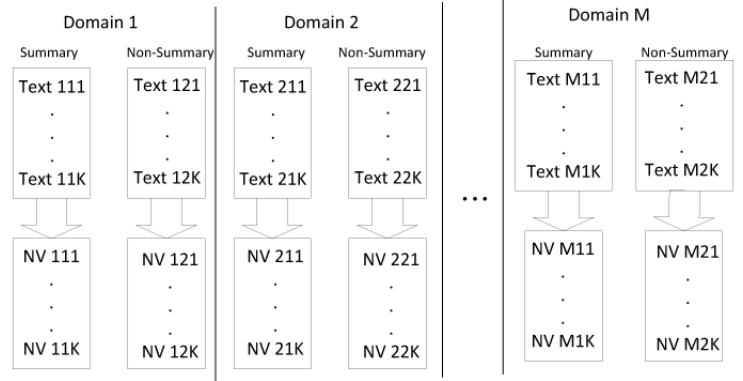


Figure 9. Preparation of Training Examples

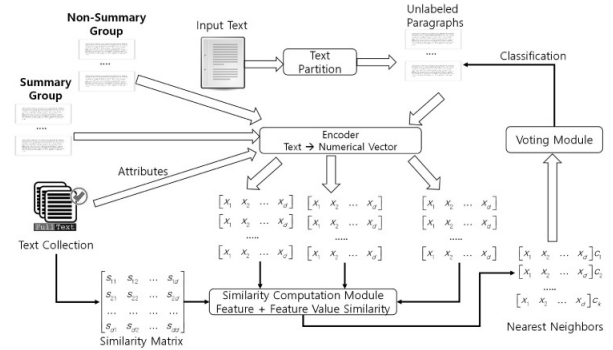


Figure 10. System Architecture

Let us make some remarks on the proposed system whose architecture is illustrated in Figure 10. The M domains are predefined, in each domain, sample paragraphs each of which is labeled with summary or non-summary are prepared, and they are encoded into numerical vectors. The paragraphs which are generated from a text are classified by one of the three variants which are described in Section III-C. The difference from the previous version of text summarization system is the ability to select one of the nearest neighbor discriminations, the attribute discriminations, and the training example discriminations. The better performance of text summarization is expected by replacing the initial

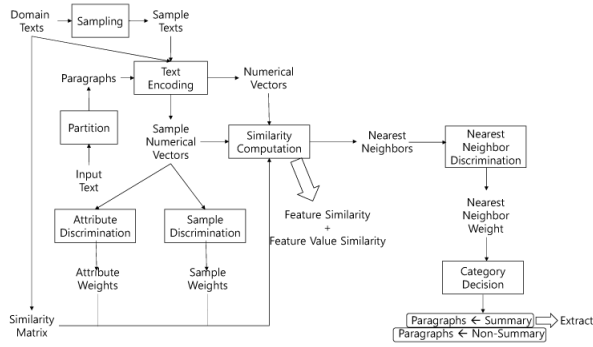


Figure 11. System Flow

KNN algorithm by its variants.

IV. CONCLUSION

Let us mention the significances of this research as the conclusion. We apply the proposed similarity metric to the KNN variants as well as the standard version. We derive the three variants from the standard version by discriminating the nearest neighbors, the attributes, and the training examples. We design the text summarization system by adopt the KNN variants with the proposed similarity metric. In the next research, we will implement the text summarization system as a real system.

Let us mention the remaining tasks as the further discussions on this research. We need to improve the high complexity in computing the proposed similarity metric by allowing only some features. We need to modify other machine learning algorithms such as the Naïve Bayes and the SVM (Support Vector Machine) by applying the proposed similarity metric. The proposed versions of the KNN variants are applied to other tasks such as the text summarization and the text segmentation. The text summarization system should be implemented by adopting the proposed KNN variants as real programs.

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